

# Variational Assimilation of Remote Sensing Data for Land Surface Hydrologic Applications

by

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Submitted to the Department of Civil and Environmental Engineering  
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## Abstract

Soil moisture plays a major role in the global hydrologic cycle. Most importantly, soil moisture controls the partitioning of available energy at the land surface into latent and sensible heat fluxes. We investigate the feasibility of estimating large-scale soil moisture profiles and related land surface variables from low-frequency (L-band) passive microwave remote sensing observations using weak-constraint variational data assimilation. We extend the iterated indirect representer method, which is based on the adjoint of the hydrologic model, to suit our application. The four-dimensional (space and time) data assimilation algorithm takes into account model and measurement uncertainties and provides optimal estimates by implicitly propagating the full error covariances. Explicit expressions for the posterior error covariances are also derived. We achieve a dynamically consistent interpolation and extrapolation of the remote sensing data in space and time, or equivalently, a continuous update of the model predictions from the data. Our hydrologic model of water and energy exchange at the land surface is expressly designed for data assimilation. It captures the key physical processes while remaining computationally efficient.

The assimilation algorithm is tested with a series of experiments using synthetically generated system and measurement noise. In a realistic environment based on the Southern Great Plains 1997 (SGP97) hydrology experiment, we assess the performance of the algorithm under ideal and nonideal assimilation conditions. Specifically, we address five topics which are crucial to the design of an operational soil moisture assimilation system. (1) We show that soil moisture can be satisfactorily estimated at scales finer than the resolution of the brightness images (downscaling), provided sufficiently accurate fine-scale model inputs are available. (2) The satellite repeat cycle should be shorter than the average interstorm period. (3) The loss of optimality by using shorter assimilation intervals is offset by a substantial gain in computational efficiency. (4) Soil moisture can be satisfactorily estimated even if quantitative precipitation data are not available. (5) The assimilation algorithm is only weakly sensitive to inaccurate specification of the soil hydraulic properties. In summary, we demonstrate the feasibility of large-scale land surface data assimilation from passive microwave observations.

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